



Validating Mobile Electroencephalographic Systems for Integration Into the PhyCORE and Application in Clinical Settings

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Executive Summary

The ability to monitor and measure brain activity patterns in individuals undergoing cognitive tasking within dynamic environments has become an emerging priority across military and neuroscientific communities, particularly those interested in real-time cognitive monitoring, rehabilitation, and training. A variety of mobile electroencephalographic recording systems have been developed to meet this demand; however, little to no published literature is available that documents efforts to validate use of these systems under complex and dynamic conditions.

This report summarizes efforts by the Naval Health Research Center to systematically test and evaluate the performance of three mobile electroencephalography (EEG) systems, in both static and dynamic conditions, as subjects performed classic visual and auditory oddball tasks within the Physical and Cognitive Operational Research Environment. The mobile EEG systems included:

1. Wearable Sensing DSI-24
2. Advanced Brain Monitoring B-Alert X24
3. ANT Neuro eego™sports 64

Data are presented on how these mobile EEG systems compared with one another, as well as against a "gold standard" wired EEG system, including data on preparation times, subjective pain and comfort ratings, and system capability to acquire high-quality EEG signals. Information is also presented on the technical integration process, with recommendations for how users might mitigate challenges associated with synchronizing the presentation of environmental stimuli with mobile EEG signal measurements with millisecond precision.

The results of this work indicated that all three mobile EEG systems were capable of acquiring high-quality EEG signals; however, significantly fewer experimental trials were needed when using the ANT system to acquire the event-related potential signal in both the resting and active conditions. The ANT Neuro system also rated high on comfort, low on pain, and within acceptable limits for preparation time. Based on these findings, it is recommended that among the three mobile EEG systems evaluated, future users should pursue the ANT Neuro eego™sports 64 mobile EEG system as the preferred choice for use in complex and dynamic environments.

Introduction

Cognitive competence, defined here as the ability to effectively perform the cognitively complex tasks associated with normal daily living, is fundamental to meeting military requirements. To evaluate the cognitive competence of our warfighters, and to advance the development of cognition-based training and rehabilitation programs, systematic investigations of cognitive competence are essential.

Of the many methods for measuring cognitive competence, electroencephalography (EEG) is among the most promising. EEG signals provide objective, real-time measurements of brain electrical activity patterns with markedly high temporal resolution.[1-6] Analyses of these signals have demonstrated that EEG systems are capable of detecting a number of neural correlates/signatures (i.e., neuromarkers) for a variety of operationally relevant cognitive functions, including fatigue, workload, and learning.[7-20]

In the past decade, the great potential of EEG measurements for monitoring and assessing cognitive competence has promoted the rapid development of mobile EEG systems capable of recording real-time brain activity in a variety of settings. These systems are marketed as inexpensive, portable, easily operable, and interpretable without technical expertise. However, most of these mobile EEG systems have not been critically evaluated in complex or dynamic environments.[21-27]

To systematically address this gap, a comprehensive investigation was carried out at the Naval Health Research Center (NHRC) in San Diego, California, to:

1. Identify the most advanced, commercially available mobile EEG systems,
2. Test and evaluate these mobile EEG systems in a highly complex and dynamic environment, and
3. Provide scientific recommendations and technical support for the transition of the validated mobile EEG system(s) to other settings within the Department of Defense (DoD).

This technical report summarizes the findings of this effort in five sections:

I. Description of the EEG Systems
II. Description of the Testing Environment
III. Integration of the Mobile EEG Systems Into the Testing Environment
IV. Validation of the Mobile EEG Systems
V. Recommendations

I. Description of the EEG Systems

Based on an extensive literature review, site visits to the vendors, and general technical inquiries, three mobile EEG systems were selected for testing and evaluation (Figure 1):

1. DSI-24 (Wearable Sensing, San Diego, CA, USA)
2. B-Alert X24 (Advanced Brain Monitoring, Inc., Carlsbad, CA, USA)
3. eego™sports 64 (ANT Neuro, Enschede, The Netherlands)

Figure 1. Top row: Wearable Sensing DSI-24; middle row: Advanced Brain Monitoring B-Alert X24; bottom row: ANT Neuro eego™sports 64.

The decision criteria for selecting these mobile EEG systems included, but were not limited to:

- Ease of use
- Durability of the hardware
- Resilience to electrical noise interference (signal-to-noise ratio)
- Stability of the acquired brain signals
- Capability of accepting external event timing markers
- Efficiency and reliability of the data acquisition and analysis software

a. Wearable Sensing DSI-24

The DSI-24 (“WS”) is a wireless, research grade, dry active electrode EEG headset. The EEG sensors are located on 21 pods featuring spring-loaded finger prongs for proper fitting (Figure 1, top row). The upper pods are connected to adjustable sway bars to provide a firm connection to the scalp for head circumferences ranging from 54–62 cm. Electrode placements follow the international 10-20 system of electrode placement. The preamplifier mounted on top of the headset samples EEG signals at 300 Hz; it then transmits the raw EEG data via Bluetooth® to a data acquisition center. The amplifier is battery operated and can run continuously if the batteries are “hot swapped” (i.e., one of the two batteries can be replaced while the system is in data acquisition mode). The WS system also features a common-mode follower circuit built into the headset to eliminate a large portion of movement artifacts.

b. Advanced Brain Monitoring B-Alert X24

The B-Alert X24 (“ABM”) features an absorbent foam and electrode gel system with 20 channels arranged on thin, flexible plastic strips (Figure 1, middle row). The plastic strips are attached to a neoprene headband and fitted using Velcro® straps to accommodate head circumferences ranging from 52–61 cm. Electrode placements follow the international 10-20 system. The preamplifier mounted on the back of the headset samples EEG signals at 256 Hz and then transmits the raw EEG data via Bluetooth® to a data acquisition center. In addition to the 20 EEG channels, four optional channels are available for measuring electrocardiography, electromyography, or electrooculography. The batteries will last 6 hours using Bluetooth® or 16 hours if data are recorded directly onto a secure digital card. A three-axis accelerometer is built into the headset for monitoring head movement and position.

c. ANT Neuro eego™sports 64

The eego™sports 64 (“ANT”) is a wet gel system with 64 electrodes embedded within a soft EEG cap, the waveguard™ (Figure 1, bottom row). Three sizes of the waveguard™ are available to fit most adult head circumferences. Each electrode is surrounded with a circular gel cup to establish an electrical connection to the scalp. Electrodes are placed according to the international 10-10 system. The amplifier is connected to a Sony tablet, both of which fit in a small backpack carried by the subject for mobility. EEG data are streamed from the amplifier directly to the tablet for storage. The sampling rate is adjustable to a maximum of 2048 Hz. The battery of the amplifier is rated to last 5 hours; however, the tablet battery lasts approximately 2.5 hours, which limits the maximum allowable recording time. The tablet communicates via Wi-Fi with a data acquisition center to control the operation of the amplifier and the data

acquisition software.

d. Brain Products BrainAmp DC 64

In addition to the three mobile EEG systems, a wired EEG system (Figure 2) was acquired to serve as a "gold standard" against which the mobile systems were validated. The wired EEG system, BrainAmp DC 64 ("BP"; Brain Products GmbH, Gilching, Germany), has been widely used in research and clinical applications (see the manufacturer's website for a list of references). Therefore, it was deemed appropriate for referencing the validation of EEG signals recorded from the mobile EEG systems. The BP is a wet gel system with 64 electrodes laid out on the EASY CAP according to the international 10-10 system. Various sizes of the EASY CAP are available to fit different adult head sizes. LED lights embedded in each electrode display different colors to indicate the electrode impedance based on preset threshold values. The LEDs also serve as land markers for three-dimensional (3-D) sensor localization using the CapTrak scanner. The electrodes are connected via wired ribbons to a control box and then to the battery powered BP amplifier. Digitized EEG signals are sent via optic fibers to the data acquisition computer. The sampling rate is adjustable to a maximum of 5000 Hz.

Figure 2. Brain Products BrainAmp DC 64.

Table 1 provides a side-by-side comparison of many of the technical features of the mobile EEG systems. Since these technologies undergo periodic updates and advancements, potential users are encouraged to visit the manufacturers' websites for the most current technical specifications.

Table 1. Technical Features of the Mobile EEG Systems

	WS	ABM	ANT
Sensor Type	Active dry sensors	Gel on absorbent foam	Gel on sensor cups
EEG Channels	20 (international 10-20 system)	20 (international 10-20 system)	64 (international 10-10 system)
Weight	700 g (headset and amplifier)	110 g (headset and amplifier)	1700 g (200 EEG cap, 500 amplifier, 500 backpack, and 500 g tablet)
Sampling Rate	300 Hz	256 Hz	Adjustable up to 2048 Hz
Battery Life	Unlimited run-time with two hot-swappable batteries	6 h using Bluetooth®; 16 h with secure digital card	5 h for the amplifier; 2.5 h for the tablet
Durability Measure	Sensor attachment bars are subject to damage if not handled carefully	Potential for creases in the plastic electrode strip and buildup of adhesive on the electrodes; the neoprene connecting the headband and electrode strip is prone to tearing	Gradual buildup of dried gel within the electrode wells if not cleaned thoroughly after each use
Mobility	Transmits up to 10 m via Bluetooth®; requires a cable for stimulus event time stamps	Transmits up to 10 m via Bluetooth®, or records directly onto secure digital card; requires a cable for stimulus event time stamps	Records directly onto tablet carried by subject; tablet is controlled via Wi-Fi; requires a cable for stimulus event time stamps
Impedance Stability	Stable throughout the recording session	Stable; progressively decreases as recording sessions continue	Stable; progressively decreases as recording sessions continue
Headset Size (Circumference)	52–62 cm	51–56 and 56–61 cm	47–51, 51–56, and 56–61 cm
Scalp Locations of Electrodes	Fp1, Fp2, Fz, F3, F4, F7, F8, Cz, C3, C4, Pz, P3, P4, T3, T4, T5, T6, O1, O2, M1, M2	Fp1, Fp2, Fz, F3, F4, F7, F8, Cz, C3, C4, Pz, P3, P4, T3, T4, T5, T6, POz, O1, O2	Fpz, Fp1, Fp2, AFz, AF3, AF4, AF7, AF8, Fz, F1, F2, F3, F4, F5, F6, F7, F8, FCz, FC1, FC2, FC3, FC4, FC5, FC6, FT7, FT8, Cz, C1, C2, C3, C4, C5, C6, T7, T8, CPz, CP1, CP2, CP3, CP4, CP5, CP6, TP7, TP8, Pz, P1, P2, P3, P4, P5, P6, P7, P8, POz, PO3, PO4, PO5, PO6, PO7, PO8, Oz, O1, O2, M1, M2

II. Description of the Testing Environment

The Computer Assisted Rehabilitation Environment (CAREN; Motekforce Link, Amsterdam, The Netherlands; Figure 3) is a fully immersive virtual reality system. The DoD presently operates four CARENs in the following centers:

1. NHRC
2. National Intrepid Center of Excellence, Bethesda, Maryland
3. Walter Reed National Military Medical Center, Bethesda, Maryland
4. Center for the Intrepid, Fort Sam Houston, Texas

Figure 3. Computer Assisted Rehabilitation Environment (CAREN) Extended model.

The CAREN Extended model at NHRC features numerous measurement and presentation upgrades from the standard model to produce clinical and operationally relevant programs. This system consists of a full motion, 9-foot-diameter platform programmable to move in 6 degrees of freedom, independently or simultaneously. At the center of the platform is a high performance (i.e., large acceleration and reverse mode), dual-belt treadmill with integrated force plates underneath to measure ground reaction forces. The platform is surrounded by a 180-degree wide and 9-foot tall curved screen, equipped with a 14-camera optical motion capture system for tracking movement of the subject. This CAREN also features three 3-D video projectors, surround sound speakers, and a programmable scent delivery device, which together provide fully immersive experiences with multimodality sensations (visual, auditory, vestibular, and

olfactory) that can be controlled by the subject or operator. Based on NHRC CAREN updates and programmatic capabilities, it has been renamed the Physical and Cognitive Operational Research Environment, or PhyCORE (Figure 4). This system provides an ideal platform for integrating, testing, and evaluating the mobile EEG systems within highly controlled, repeatable, and dynamic task conditions.[28,29]

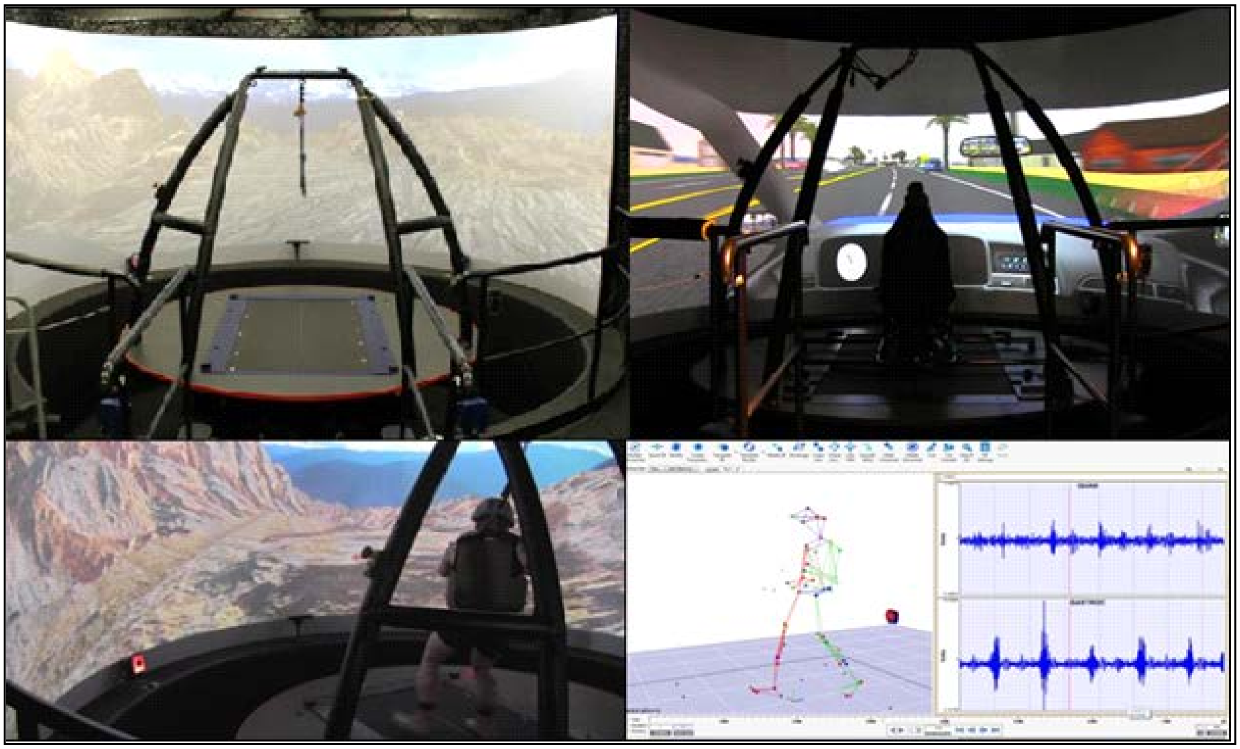

Figure 4. The Physical and Cognitive Operational Research Environment (PhyCORE; top left), with custom driving simulator (top right), military-relevant scenarios (bottom left), and multiple biosensors providing real-time monitoring and measurements (bottom right).

III. Integration of the Mobile EEG Systems Into the Testing Environment

To effectively evaluate the performance of the mobile EEG systems, the first task was to establish digital communication pathways through which the recorded EEG signals could be accurately time stamped with events occurring in the PhyCORE. Technical challenges associated with this integration process included:

1. Establishing a mechanism by which the PhyCORE Control Center could transmit event signals,
2. Customizing the process by which each mobile EEG system would receive event time stamps, and
3. Calibrating the timing accuracy and jitters embedded in the established digital signal pathways.

Approaches for overcoming these technical challenges were presented at the 2015 Interservice/Industry Training, Simulation and Education Conference (I/ITSEC) in Orlando, Florida, and published in the conference proceedings (Appendix A). Main solutions are summarized below.

The greatest technical challenge in integrating the mobile EEG systems into the PhyCORE was determining how to time stamp the EEG signals with PhyCORE events. Practical solutions depended heavily on how the event signals were transmitted from the event generators and how the signals were received by the EEG systems. Complications arose from the inherent design differences among the mobile EEG systems, since each system had unique methods for achieving mobility and synchronizing external events with the EEG signals.

As depicted in Figure 5, for the ABM system, EEG signals were acquired in the headstage unit and transmitted via Bluetooth® to an External Sync Unit for time stamping the EEG signals. The time stamped EEG signals were then streamed into the data acquisition center through a USB cable. However, the use of Bluetooth® transmission prior to time stamping created an unavoidable time delay (T_{blue}) of approximately 35 ms and averaged jittering of 20 ms, as reported by the manufacturer. In contrast, the external event signals for both the WS and ANT systems were sent directly to an EEG amplifier through a cable connected to the event generator (PhyCORE Control Center). Thus, for these systems, EEG signals were time stamped prior to their wireless transmission to the data acquisition computer. This method effectively eliminated the T_{blue} found with the ABM system.

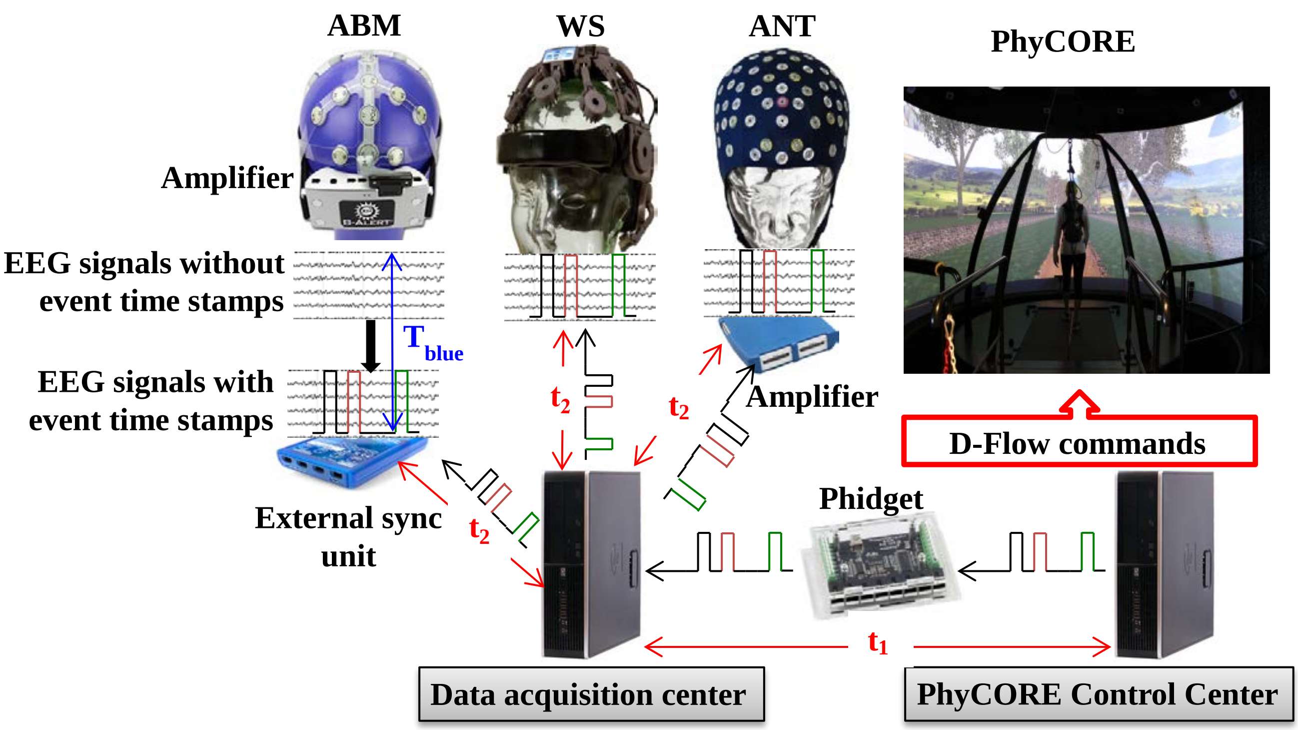

Figure 5. Technical approach diagram for integrating the mobile EEG systems into the PhyCORE.

From the event generator, events such as platform movement, treadmill speed, and stimulus presentation were all programmed and produced with a software program called D-Flow (Motekforce Link, Amsterdam, The Netherlands). By design, D-Flow does not communicate with the computer's parallel ports. Therefore, to send PhyCORE event time stamps to the EEG systems, a 1018 Phidget I/O Board (Phidgets Inc., Calgary, Alberta, Canada) was used to receive event time stamps via a USB port. This particular board can input digital or analog signals and provide a digital output through a USB cable. The Phidget I/O Board sent the event time stamps to a PCI-based digital I/O board residing in the computer of the data acquisition center. Only then could the event time stamps be relayed to the EEG systems through the parallel ports. Inevitably, this event timing transmission method created a systematic delay (T_{sys}) in the time stamping of EEG signals ($T_{sys} = t_1 + t_2$). This T_{sys} was independent of the design of the EEG systems and was, therefore, consistent for all three systems. Using this approach, the total delay in event timing for the WS and ANT systems was T_{sys}. For the ABM system, the total delay was $T_{sys} + T_{blue}$ (equivalent to $t_1 + t_2 + T_{blue}$).

The existence of time delays was inevitable due to technical restraints; nevertheless, the value of T_{sys} could be measured accurately. As shown in Figure 6, T_{sys} was calibrated using a trigger box manufactured by Wearable Sensing. The actual timing (T_{act}) of the PhyCORE screen's visual

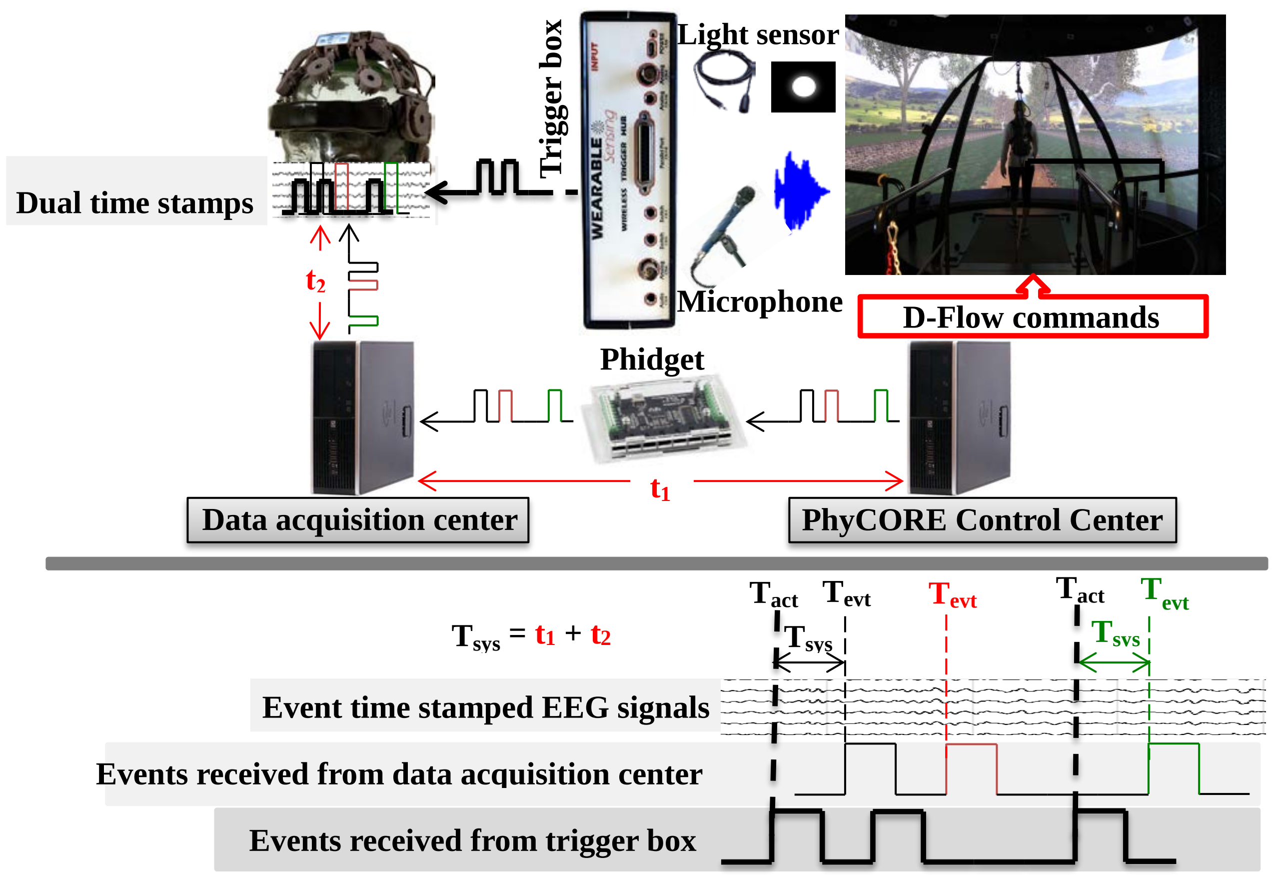

Figure 6. Calibration of event time delays and jitters.

display or the surrounding speakers' sound emission was detected by a light sensor or microphone connected to the trigger box. The trigger box then sent the visual or audio event signal to the headstage (Figure 6, top). Simultaneously, the event marker signals sent to the EEG system from the data acquisition center were also sent to the headstage and recorded as T_{evt}. The values of T_{sys} were then measured off-line by calculating the difference between T_{evt} and T_{act} (Figure 6, bottom). The mean values of T_{sys} were 21.9 ms and 30.7 ms for the visual and auditory stimulation, respectively. These T_{sys} values were accounted for in EEG data analyses for both the WS and ANT systems. For the ABM system, an additional 35 ms (T_{blue}) were used to compensate for the delay. Further, for each system, there was a fixed time delay associated with the EEG signal digitization in the amplifier that needed to be taken into account during data analyses. The duration of this delay varied by system and was made available by each of the system manufacturers.

In summary, a technical framework for integrating the mobile EEG systems into the PhyCORE with millisecond time synchronization was established through execution of this project. The three mobile EEG systems tested in this work represent the full technical scope of how EEG signals are acquired, wirelessly transmitted, and time stamped in the industry. This approach for integrating mobile EEG systems, although developed specifically for the PhyCORE, can be generalized and adapted by other types of immersive virtual reality enviornments, CARENs, and clinical settings.

IV. Validation of the Mobile EEG Systems

The ultimate goal of implementing mobile EEG systems into the PhyCORE was to determine whether, and to what degree, these systems could detect behaviorally relevant EEG signals under highly complex and dynamic conditions. To this end, a research proctocol titled "Validating Mobile EEG Systems for Integration Into the PhyCORE and Application in Clinical Settings," was developed and approved by the institutional review board at NHRC (Protocol NHRC.2014.0017). Preliminary analyses from this study were published in the 2015 I/ITSEC conference proceedings as a paper (Appendix A) and presented as three conference posters (Appendixes B–D). The results of these authored works and additional findings are detailed below.

a. Method of Assessment

Twelve healthy volunteers participated in the study (7 women, 5 men, age range: 21–40 years). Subjects reported individually to NHRC's PhyCORE laboratory. They were informed that with their consent they would be fitted with three different mobile EEG headsets and undergo similar testing trials on the PhyCORE, while wearing each system. After donning each headset, an impedance check was performed in accordance with each vendor's impedance test utility tool to ensure all channel connections were satisfactory. Following testing of each system, subjects completed a brief survey evaluating their levels of pain and comfort using rating scales and open-ended questioning for each factor. Short breaks (10–20 min) were taken between testing conditions, in addition to a 1-hour lunch break. Time to complete the entire experiment was approximately 8 hours.

Testing trials consisted of classical auditory and visual oddball experiments performed under two

conditions: (1.) *Resting*: subjects sat still on a chair located on the stationary PhyCORE platform with a visual display of a stationary nature trail scene; and (2.) *Active*: subjects walked at a self-selected pace on the PhyCORE treadmill with a visual display of a dynamic nature trail scene that flowed in sync with their walking speed. Due to extensive wiring, trials with the BP system were only completed in the resting condition. Preceding each testing trial, a baseline assessment of each subject's EEG activity was acquired while the subject sat with eyes opened and then closed for 2 min each.

For the auditory oddball paradigm, a series of bird chirps was presented through the surround sound speakers as the frequent stimulus, and toad croaks as the rare stimulus. For the visual oddball paradigm, a bird image was displayed at the center of the screen as the frequent stimulus, with a display of a toad image as the rare stimulus. Presentation of frequent to rare stimuli occurred at a 4:1 ratio. The stimulus duration was 0.5 s, and the stimulus interval varied pseudo-randomly between 1.5–2.0 s. The rare stimuli were presented pseudo-randomly following presentation of 2–10 frequent stimuli. A total of 250 (200 frequent, 50 rare) and 500 (400 frequent, 100 rare) stimuli were presented in each session for the sitting and walking conditions, respectively, which corresponded to about 10 min for each sitting trial and 20 min for each walking trial. For all trials, subjects were instructed to silently count the total number of frequent stimuli and report this total at the end of each session.

b. Operational Feasibility Evaluation

Preparation and Cleanup Time

The preparation time for each mobile EEG system was defined as time elapsed from initiation of the fitting process to completion of the impedance check. The average time duration to complete each of the preparation stages for each system is summarized in Figure 7. Overall, the dry

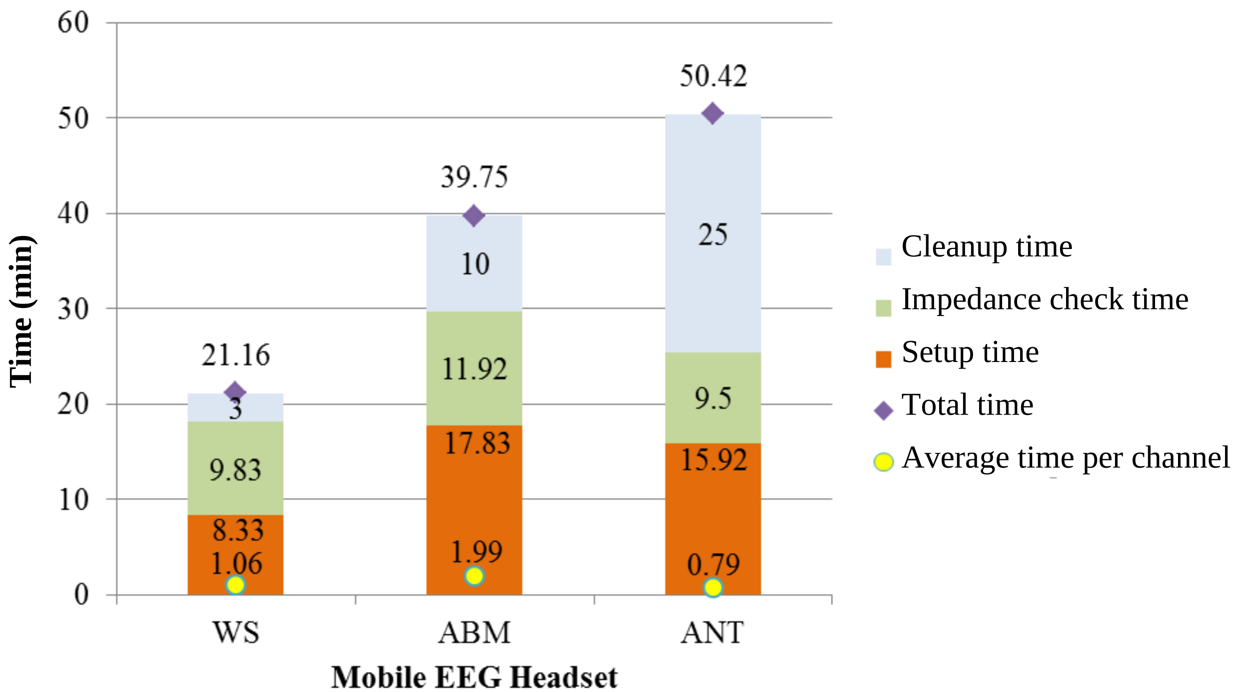

Figure 7. Mean preparation and cleanup times for the mobile EEG systems.

electrode WS system required less total preparation time than the other two wet electrode systems. Despite large differences in the number of channels, preparation time for the ANT system (setup + impedance check = 25.4 min) was slightly shorter than that for the ABM system (average 29.8 min). However, the cleanup time for the ANT system (average 25 min) was much longer than the other two systems (ABM, 10 min; WS, 3 min), most of which was spent on brushing the gel out of each of the 64 electrode cups. Nonetheless, among the three mobile EEG systems, the averaged total time (preparation and cleanup) spent on each channel was lowest for the ANT system. Thus, the ANT system was the most time-efficient system with respect to preparation and cleanup.

Pain and Comfort Ratings

After testing each of the three mobile EEG systems, subjects completed rating scales to indicate their levels of pain, ranging from 0 (*no pain*) to 10 (*extreme pain*), and comfort, ranging from 0 (*very uncomfortable*) to 5 (*very comfortable*), experienced with each system. Means and standard deviations for these assessments are presented in Table 2 and Figures 8 and 9.

Results of separate one-way analyses of variance yielded statistically significant differences in comfort ($F(2, 33) = 10.07$, $p < 0.001$) and pain ($F(2, 33) = 13.79$, $p < 0.001$) ratings among the headsets. Games–Howell post hoc testing indicated the WS system rated significantly higher on the pain scale than the ABM and ANT systems (both $p < 0.05$); however, the mean pain rating for the WS system (2.17 on a 10-point scale) was still fairly low. This suggests that although the WS system rated higher on the pain scale, it was not necessarily rated as painful. The mean pain score comparison between the ABM and ANT systems was not statistically significant (in fact, they were identical). For the comfort scale, the Games–Howell post hoc test indicated the WS system was rated significantly less comfortable than the ABM and ANT systems (both $p < 0.05$); the latter of which, again, did not significantly differ.

Effect size analyses (Cohen's *d*) were conducted on all statistically significant findings to determine the degree to which pain and comfort ratings for each system differed in terms of practical significance (0.2, small effect; 0.5, medium effect; 0.8, large effect). Based on these analyses, the WS system was rated as considerably more painful than the ABM (d = 1.33) and the ANT ($d = 1.43$) systems and considerably less comfortable (ABM, $d = 1.77$; ANT, $d = 1.37$). These large effect size estimates support the notion that subjects expressively rated the WS system as more painful and less comfortable than the ABM and ANT systems based on their user experience.

Table 2. Pain and Comfort Ratings

Mobile EEG System	**Pain Rating M (SD)**	**Comfort Rating M (SD)**
WS	2.17 (1.85)	3.17 (1.27)
ABM	0.25 (0.87)	4.83 (0.39)
ANT	0.25 (0.45)	4.50 (0.52)

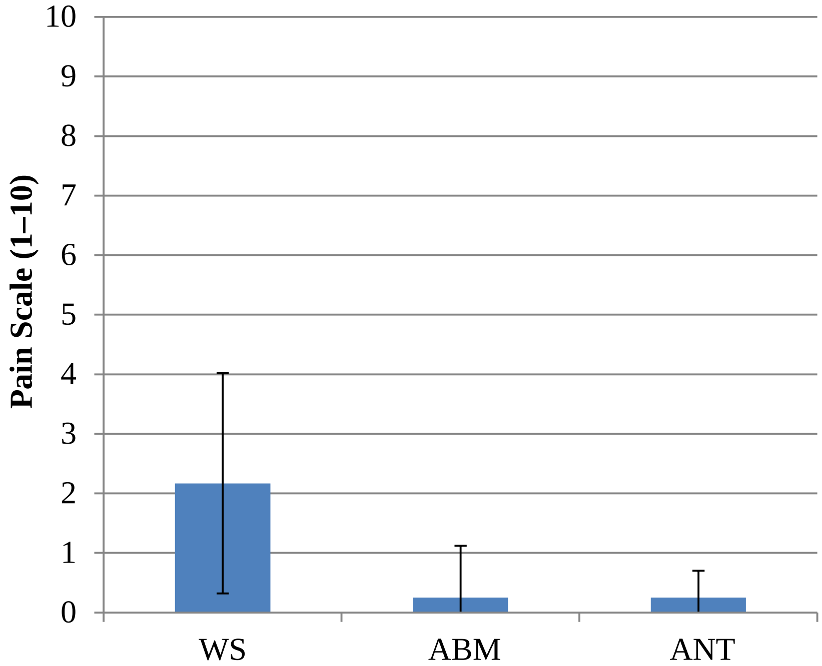

Figure 8. Perceived pain ratings.

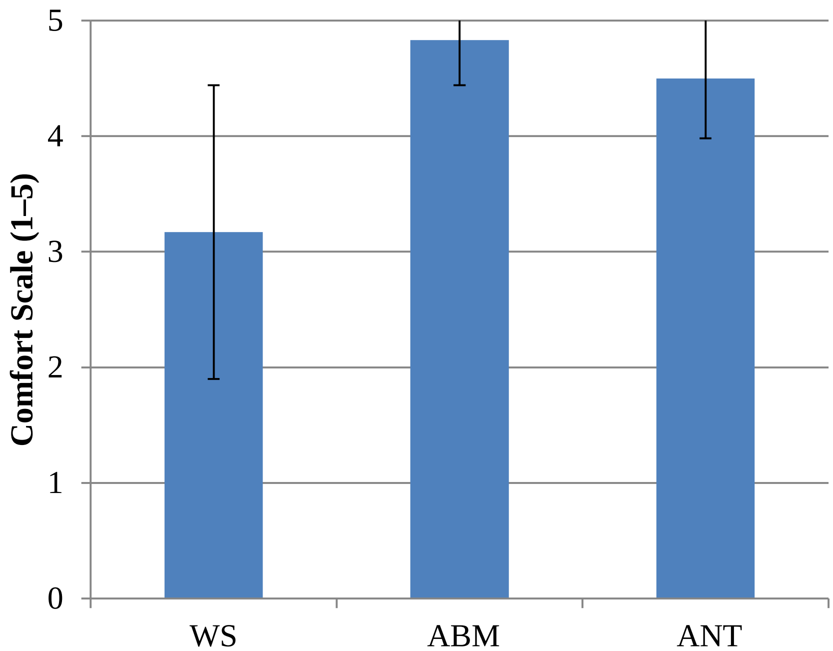

Figure 9. Perceived comfort ratings.

c. EEG Signal Quality Assessments

Consistent with analyses performed in the EEG literature,[30,31] the grand average event-related potential (ERP) was computed for each mobile EEG system. The ERP waveforms used in these analyses were obtained by averaging multiple EEG epochs temporally aligned to auditory or

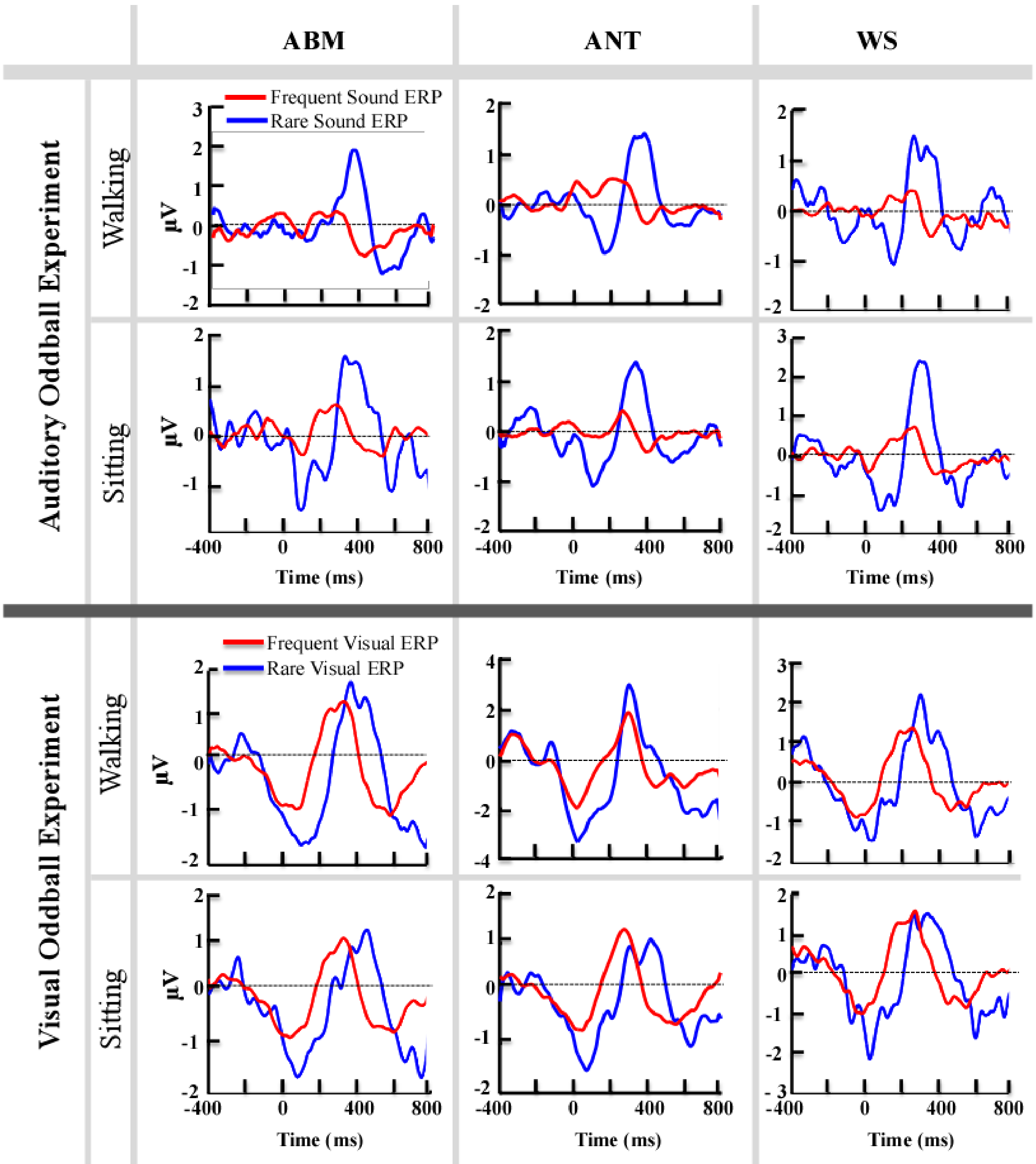

Figure 10. Across mobile EEG systems, comparisons of the grand average ERPs acquired under both sitting and walking conditions from the auditory (top panel, sensor F3) and visual (bottom panel, sensor P4) oddball experiments from all 12 participants.

visual stimuli presented in the PhyCORE. Through this process, random and event-uncorrelated electrical noises were averaged, and the underlying phase-locked ERP waveforms were revealed. As depicted in Figure 10, all three mobile EEG systems yielded adequate quality and behaviorally relevant ERP waveforms.

In theory, any electric signal sensor placed on the scalp can be used to measure ERP, given sufficient repetitions of stimulus presentation or motor actions. In practice, however, there is often neither time nor resources to allow for the hundreds or even thousands of events that may be necessary to acquire a compelling ERP measurement; therefore, only those EEG systems that require the fewest stimulus presentations or motor actions to generate ERP have the most pragmatic value. Therefore, we performed usability analyses on the three mobile EEG systems to compare the number of stimulus presentations required for each system to measure ERP. To assess usability of the three systems, judged by the EEG measurement reliability and ERP quality assurance, a two-step bootstrap method was developed to estimate: (1) the minimal number of trials required for detecting the presence of ERP, and (2) the optimal number of trials needed to obtain high-quality ERP.

To quantify the overall strength of the ERPs in the auditory and visual oddball paradigms, an ERP index (*idx*) was calculated from the formula:

$$idx = \frac{\mathrm{Post_{RMS}} - \mathrm{Pre_{RMS}}}{\mathrm{Post_{RMS}} + \mathrm{Pre_{RMS}}}$$

where, $\mathrm{Post_{RMS}}$ was the root mean square (RMS) of the ERP amplitude within the 800 ms time window after onset of the sensory stimulus, and $\mathrm{Pre_{RMS}}$ was the RMS within the 400 ms time window before onset of the sensory stimulus. A value of $idx < 0$ indicated the absence of ERP, $idx = 0$ suggested no more ERP signal than noise, and $idx > 0$ signified the presence of ERP. The extreme values of *idx* ranged from −1 to +1 corresponding to $\mathrm{Post_{RMS}} = 0$ and $\mathrm{Pre_{RMS}} = 0$, two unachievable conditions, respectively.

An example of ERP obtained from the active auditory oddball paradigm recorded with the WS system is shown in Figures 11A and 12A. EEG epochs aligned with the onset of sound stimuli, including both frequent and rare stimuli, were averaged to reveal the underlying ERP waveform. The ERP index value ($idx = 0.469$) was closely associated with the high-quality ERP waveform shown in the bottom panel of Figure 11A and Figure 12A.

A single-point measurement of *idx*, however, does not provide any information about the variability of EEG signals recorded with the same or different EEG systems; therefore, it could not be used to assess the mobile EEG systems' usability (i.e., EEG measurement reliability and ERP quality assurance). A two-step method based on bootstrap resampling was developed to achieve this objective (Figure 11).[32–44]

Step One: Bootstrap resampling of randomly selected samples (*S*) out of the number of EEG epochs (*N*) (Figures 11B and 11C) yielded an *idx* probability distribution of ERP waveforms for a single EEG channel (Figure 11D). The 95% confidence interval (*idx–CI*) was computed based on this probability distribution. The lower bound of this *idx–CI*, the $\mathrm{LB_S}$, provided an assessment of EEG measurement reliability for yielding an ERP signal in a single EEG channel:

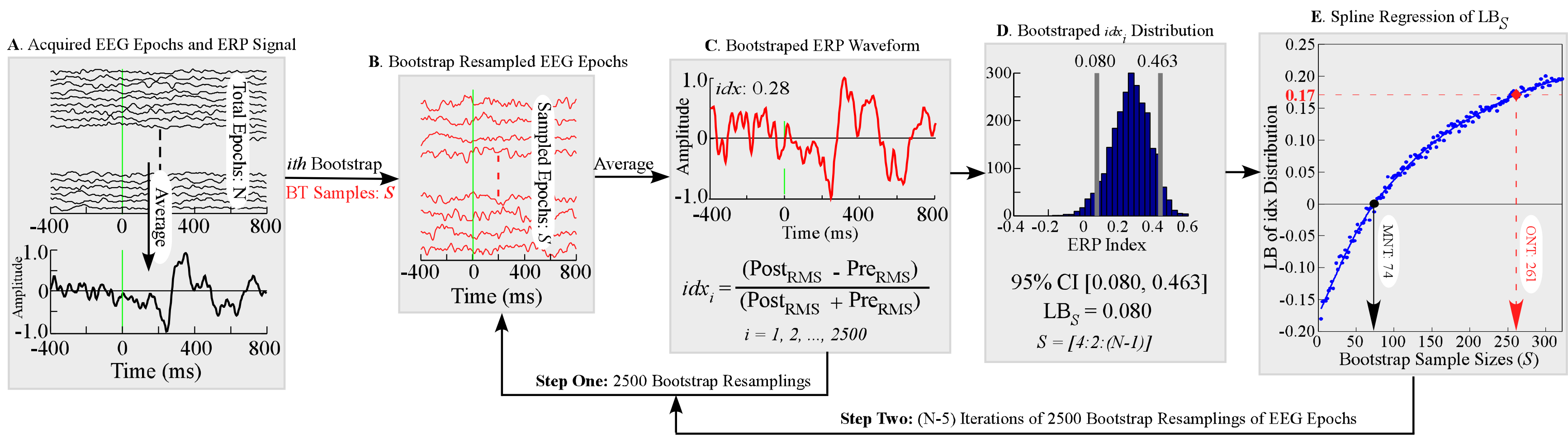

Figure 11. Two-step bootstrap method for estimating the minimal number of trials (MNT in E) required for detecting ERP and the optimal number of trials (ONT in E) necessary for obtaining high-quality ERP. The green vertical line indicates onset of the stimuli. ***ith* Bootstrap**: the *ith* of the 2500 bootstraps. **BT Samples**: the *ith* bootstrap with bootstrap sample size *S*. See text for details.

- $LB_S < 0$, unreliable EEG measures and ERP absence
- $LB_S > 0$, reliable EEG measures and ERP presence

The value $LB_S = 0$ can thus serve as the threshold for determining the minimal number of trials (MNT) required for detecting the presence of ERP.

Step Two: The bootstrap resampling process outlined in step 1 was iterated multiple times with different resampling sizes. The total number of iterations (i.e., number of bootstraps) was determined by the step function: [4: 2: (N-1)] (minimal S = 4, maximal S = N-1, step size = 2, total iterations = (N-5)/2). A spline regression of the resulting set of LB_S values as a function of resampling size S was performed to estimate:

1. The MNT required to detect the presence of ERP: bootstrap resampling size S corresponding to $LB_S = 0$ (Figure 11E), and
2. The optimal number of trials (ONT) needed to obtain high-quality ERP: bootstrap resampling size S corresponding to $LB_S = 0.170$ (Figure 11E).

The value $LB_S = 0.170$ was calculated based on the estimated minimal signal-to-noise ratio ($Post_{RMS}/Pre_{RMS}$ = 3 dB) of the ERP waveform to be considered a high-quality signal as reported in the literature.[45-49]

Figure 12 depicts the relationship between ERP quality and LB_S values. With $LB_S < 0$ (Figure 12B), the bootstrap ERP waveforms (averaged across 4 EEG epochs) did not assemble at all to the acquired ERP waveform (averaged across all 322 EEG epochs, Figure 12A). When $LB_S = 0$ (Figure 12C), the major features of the acquired ERP waveform appeared clearly on all three examples of the bootstrap ERP waveforms. With $LB_S = 0.170$ (Figure 12E) and halfway between 0 and 0.170 ($LB_S = 0.080$, Figure 12D), detailed patterns of major components of the acquired ERP waveform became clearly visible. Thus, in order to assess usability of the mobile EEG systems, the bootstrap sample sizes corresponding to the values $LB_S = 0$ and $LB_S = 0.170$ were used as objective measures for determining the MNT required for detecting ERP and the ONT needed to acquire high-quality ERP waveforms, respectively.

The MNT required for detection of ERP for all 20 common channels across the 12 subjects in both the auditory and visual oddball paradigms were compared separately under resting and active conditions (Figure 13A). In the resting condition, the MNT for the WS and ABM systems were comparable (WS: 117 ± 16 SE, n = 123; ABM: 116 ± 12 SE, n = 141; Wilcoxon rank sum test: $p = 0.6661$), and both were significantly higher than the MNT for the ANT (71 ± 12 SE, n = 136; $p < 0.0001$ for both WS vs. ANT and ABM vs. ANT) and BP (62 ± 8 SE, n = 60; $p < 0.0001$ for both WS vs. BP and ABM vs. BP) systems. In contrast, the MNT for the ANT system was slightly higher, but not statistically different, than the MNT for the BP system ($p = 0.4233$). Thus, in the resting condition, the ANT system required approximately the same number of trials for detecting ERP signals as the gold standard wired EEG system (i.e., BP), while the WS and ABM systems required significantly more trials for detection to the same degree. Similarly, in the active condition, the MNT for the ANT system was significantly lower than the MNT for

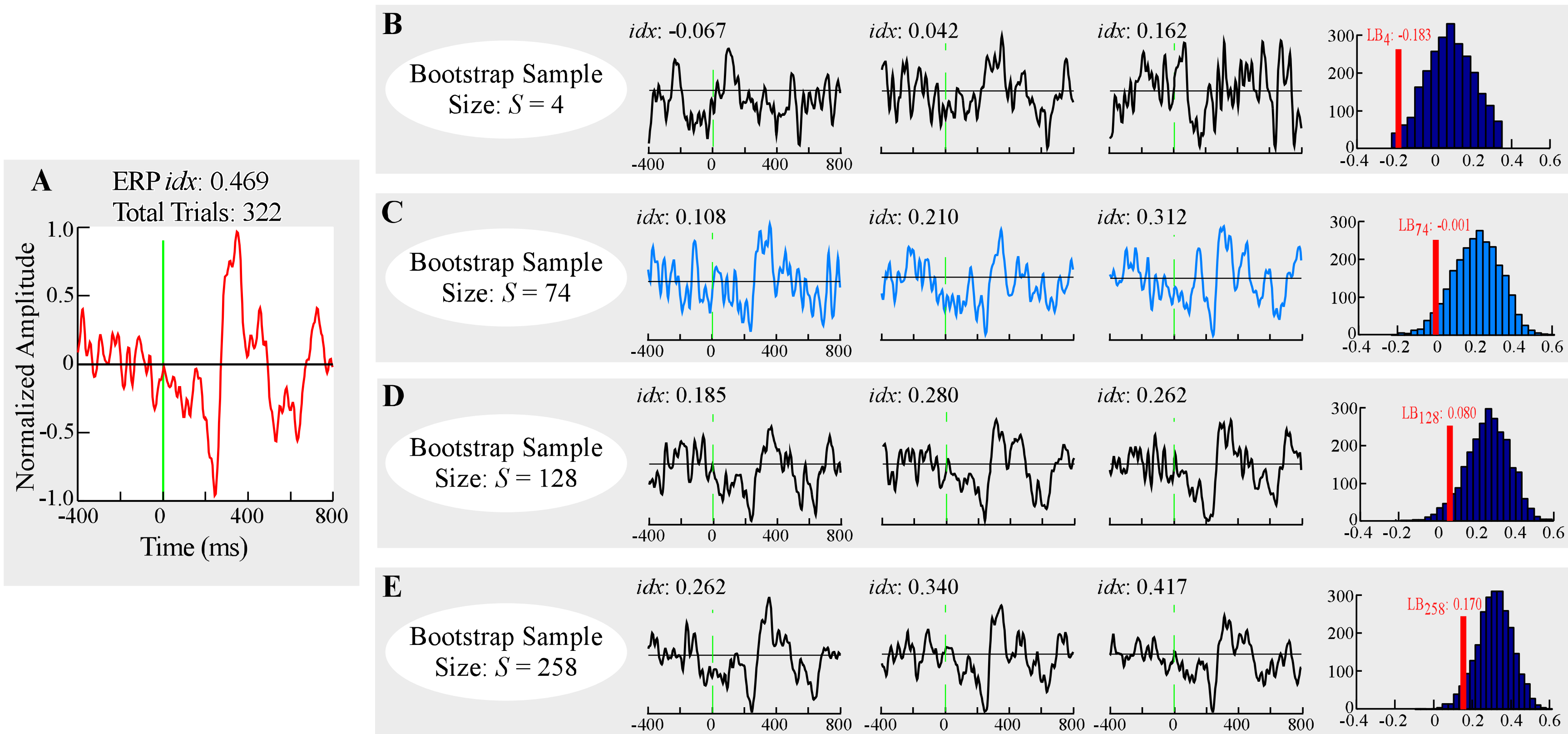

Figure 12. Example of bootstrapped ERP waveforms in step 1 the two-step method on a single EEG channel, illustrating the correlations between the qualities of ERP waveforms and the lower bound (LB) values of the ERP index distribution. In this example, the MNT for detecting ERP was 74, as determined by the value of $LB_{74} = 0.0$ (emphasized with blue in Panel C). Vertical green lines indicate onset of the stimuli. See text for details.

both the WS and ABM systems (WS: 199 ± 12 SE, n = 161; ABM: 175 ± 11 SE, n = 148; ANT: 147 ± 14 SE, n = 132; p < 0.0001 for both WS vs. ANT and ABM vs. ANT).

Since the MNT for detecting ERP presence is directly related to the EEG measurement reliability and signal quality, the ONT for obtaining high-quality ERP would be expected to be lower in a system with lower MNT for detecting ERP presence. As depicted in Figure 13B, the ONT for the ANT system was indeed significantly lower in both the resting and active experimental conditions than the ONT for both the WS and ABM systems (resting WS: 192 ± 22 SE, n = 53; ABM: 171 ± 19 SE, n = 51; ANT: 128 ± 17 SE, n = 96; p < 0.0001 for both WS vs. ANT and ABM vs. ANT; active WS: 275 ± 20 SE, n = 84; ABM: 279 ± 15 SE, n = 80; ANT: 176 ± 15 SE, n = 95; p < 0.0001 for both WS vs. ANT and ABM vs. ANT). In the resting condition, the ONT for the ANT system was slightly higher than that for the BP system (ANT: 128 ± 17 SE, n = 96; BP: 115 ± 12 SE, n = 36), but this difference was not statistically significant (p = 0.2634).

Using two-step bootstrap resampling of real data recorded from the three mobile EEG systems and a wired gold standard EEG system, a fully objective and statistically rigorous method was established for assessing EEG measurement reliability and ERP quality assurance with two simple and straightforward parameters: the MNT for detecting ERP presence, and the ONT for acquiring high-quality ERP. Across all experimental conditions, the ANT mobile EEG system showed significantly higher levels of usability than the other two mobile EEG systems when

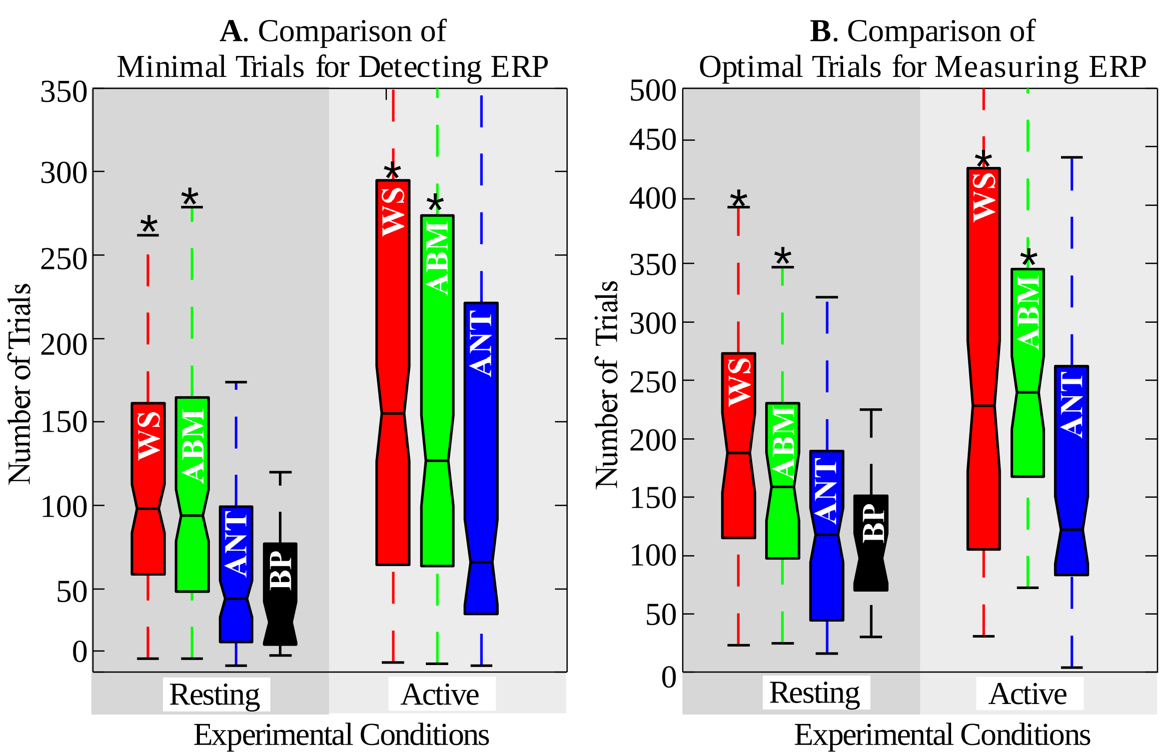

Figure 13. Comparisons of the MNT required for detecting ERPs and the ONT necessary for obtaining high-quality ERPs under resting and active conditions. The horizontal line in the center of each notch indicates the median value. *Indicates p < 0.0001 in Wilcoxon rank sum tests of WS vs. ANT and BP, and ABM vs. ANT and BP in both experimental conditions.

evaluated with both objective parameters (Figure 13). It is thus evident that, at least with respect to the reliability of EEG signal measurements and the assurance of ERP quality, the ANT system was superior to the WS and ABM systems. Furthermore, the ANT system was statistically comparable to the gold standard wired BP system.

V. Recommendations

In the current project, three mobile EEG systems were successfully integrated into the PhyCORE at NHRC for testing and evaluation. The performance of these systems was systematically evaluated with respect to their practical use and capability for acquiring high-quality EEG signals in a highly dynamic environment.

From a technical integration standpoint, we observed that the ABM system exhibited a systematic timing delay inherent to the manufacturer's system configuration (Figure 4, T_{blue}). Although this added delay could be compensated for in off-line data analyses, it could be potentially problematic for applications in which online EEG data processing is required, such as brain–computer interface applications.

With regard to system setup, system preparation times appeared to be a function of both the electrode type (i.e., dry vs. wet) and number of channels. The dry electrode WS system required the least amount of total time to prepare. However, it should be noted that the ANT system (which features the most channels) required the least amount of time per channel to prepare. If preparation time is a consideration, and/or not all EEG channels are needed for a given protocol, it is possible to activate only those channels for which the user is most concerned. In such a circumstance, based on the average preparation time by channel, the ANT system offered the most practical solution.

Analyses of the pain and comfort data indicated that the WS system received higher pain ratings and lower comfort ratings than the other two systems. Further, although the ABM and ANT systems were rated equally low on the pain scale, the ABM system received the highest comfort ratings overall.

With respect to the reliability of EEG signal measurement and the assurance of ERP quality, the ANT system was clearly superior to both the WS and ABM systems. Although all three mobile systems demonstrated the capability to acquire high-quality EEG signals, significantly fewer experimental trials were needed when using the ANT system to acquire the ERP signal in both the resting and active conditions. It is particularly notable that the ANT system performed almost as well as the gold standard wired BP system in recording highly reliable EEG signals in the resting condition.

Based on these findings, we recommend that of the three mobile EEG systems evaluated, future users should pursue the ANT Neuro eego™sports 64 mobile EEG system as the preferred choice for use in complex and dynamic environments. As newer mobile EEG systems are developed and commercialized, they should be evaluated in a similar manner for comparison with the systems presented here.

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VIII. Appendixes

A. Cox BD, Edwards HM, Service KA, Sessoms PH, Dominguez JA, Zheng W, et al. Toward cognitive two-way interactions in an immersive virtual reality environment. Paper presented at: Interservice/Industry Training, Simulation, and Education Conference; November 30-December 4, 2015; Orlando, FL.
B. Zheng W, Service K, Markham A, Reini S. Recording auditory and visual evoked responses with mobile EEG systems in a Computer Assisted Rehabilitation Environment (CAREN). Poster presented at: Experimental Biology Conference; March 28-April 1, 2015; Boston, MA.
C. Cox BD, Service K, Reini S, Zheng W. Assessing objective neuromarkers in an immersive virtual reality environment. Poster presented at: Military Health System Research Symposium; August 17-21, 2015; Fort Lauderdale, FL.
D. Cox BD, Zheng W, Service K, Aftreth J, Sessoms P. Validating mobile EEG systems for cognitive monitoring, rehabilitation, and training in complex and dynamic environments. Poster presented at: Military Health System Research Symposium; August 15-18, 2016; Kissimmee, FL.

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14. ABSTRACT
This report documents technical and research efforts to systematically compare the performance of three mobile electroencephalographic (EEG) systems within the Naval Health Research Center's Physical and Cognitive Operational Research Environment. Twelve healthy subjects performed classic auditory and visual oddball tasks in both static (sitting) and dynamic (walking) conditions while wearing each mobile EEG system (subjects also wore a "gold standard" wired EEG system in the static condition only). Results indicated that all three mobile EEG systems were capable of acquiring high quality EEG signals; however, there were significant differences based on system preparation times, ratings of pain and comfort, and number of trials required to achieve measurement quality comparable to the "gold standard" system.

15. SUBJECT TERMS
electroencephalography (EEG); Computer Assisted Rehabilitation Environment (CAREN); Physical and Cognitive Operational Research Environment (PhyCORE); cognitive monitoring

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